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# A Procedure to Predict the Energy Demand Profile of District System

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## Abstract

*The ever-increasing demands for heating in different sectors, along with more preventative regulations on greenhouse emissions, have compelled designers to seek new alternatives to design energy-efficient buildings. One of these alternative approaches is the Community-District System (CDS). Different methods have been proposed for improving the energy efficiency of CDSs. One of these methods focusses on decreasing peak demand load and regulating energy consumption via energy management. In order to implement this approach it is essential to predict the detailed energy consumption profile of the CDS.*

*Several methods have been developed to model the demand profiles of CDSs. In a small-scale systems, due to the small number of users, the energy demand profile will be predicted by the detailed-modeling of the users using different energy simulation software whereas in large district scale system, due to large volume of users, a comprehensive modeling of the users is time consuming and can be unfeasible.*

*To overcome this problem, a variety of simplified models have been developed and utilized by designers. One of the main drawbacks of the existing simplified models is that they mostly determine the total energy consumption of the users as opposed to the detailed annual profile of the energy consumption.*

*This paper describes the development of procedure to predict the energy consumption profiles of the large-scale CDS. This model have been validated by comparing the model prediction with the results obtained from simulation of the community scale CDS using comprehensive model.*

**Keywords – Energy simulation; Simplified Model; District Heating System; Energy Demand Profiles**

## 1. Introduction

Several strategies in energy production, conversion, and user-side demand have been proposed to conserve energy in building sectors. In addition to these ones, one of the viable solutions is to move to a more efficient way of energy sharing and management at community level – community district

system (CDS). The idea of CDS is to integrate buildings, renewable energy sources, energy storage (ES), and utility grids. This integration can provide energy security, and help to reduce GHG while providing new technologies/services in developing energy systems, and decoupling the supply and demand sides. There are, however a number of challenges in the design, construction and operation of such system. In order to design the efficient CDS the first step is to design the demand profile of the users. Having the more accurate, detailed demand profile could result in better management and as a result higher efficiency of the CDS.

Designers model the users' network based on the energy profiles of the buildings, irrespective of the building type, characteristic, and user types. Since building heterogeneity in each DS is elevated, particularly in the urban setting, and each building has its unique properties and specific demand profile, it is essential to develop a model that can predict the demand profile of the entire district with acceptable accuracy. Different methods suggested in the literature in order to model or predict the users' demand profile are in three major streams: Deterministic methods (comprehensive or simplified), Statistical methods and Predictive methods. Many of these methods predict the energy consumption of buildings in terms of the total energy consumption and maximum demand while others predict the actual profile of the system in smaller intervals such as an hourly basis. One of the most important criteria in choosing the type of model used for predicting the energy demand profile of the system is the size of the CDS. For example, for a smaller CDS, comprehensive modeling could be used while simplified deterministic model is better adopted for a larger scale system. Although yielding highly accurate demand profiles, the main disadvantages of the comprehensive models are their requirements in terms of data quantity and time for modeling each building. Despite this fact, Zhang [1] used the comprehensive method for modeling the demand profile of 95817 in Westminster, UK. Different simplified deterministic models are suggested by researchers: For instance, Kim et al. [2] used a simplified deterministic method that take into account parameters such as shape, orientation and occupancy type to predict an average energy required per square meter of a building area based on its monthly/yearly outdoor design temperature. Wang and Xu [3] used a simplified physical method to predict the demand profile load including the effect of thermal mass on load prediction by the means of a generic algorithm. Al-Homoud [4] compared the Degree Day (DD) method with the Bin method and concluded that in cases where the main source of energy loss is the envelope of the building, the DD method could be used. He also concluded that for larger scale buildings, in which the internal load generation has a higher effect, the Bin method has better results. Yao and Steemers [5] also developed a model to predict the load profile of domestic

buildings in the UK considering the effect of the occupants. Barnaby and Spitler [6] used energy intensity and load factor in their model for load prediction based on different user sectors of the CDS and compiled them together to predict the users' demand profile. Lei et al. [7] used a linear regression method in order to determine a useful parameter that could be used as an input data for modeling schools while Filipino [8] used a multivariate regression method in evaluating the heating demand profile of a residential sector. Another statistical method used for predicting the demand profile of the CDS is suggested by Cheng [9], who used the data from 16194 buildings in the UK in to predict the demand profile of the network.

When modeling the demand profile of users in a large scaled system, it is important to find its exact demand profile. This is objectively almost impossible due to the level of - uncertainty to model occupants' behaviour, however due to variety of the users existing in the network most of the uncertainties will be canceled out automatically. In a smaller DS, more similar patterns of usage can be found between different occupants and consequently a more accurate modeling is required.

This paper describes the development of a simplified procedure to predict the demand profile of users of CSD.

## 2. Methodology:

Energy consumption of a building is a complex phenomenon consisting of different variables.

$$\dot{Q}_{total}(t) = \sum_1^N \dot{q}_{bldg\ assemblies}(t) + \dot{q}_{sol}(t) + \dot{q}_{intrt\ gain}(t) + \dot{q}_{inf}(t) \quad (1)$$

Even though different studies have been done in this area for predicting the energy consumption of buildings, they mostly focused on the total energy consumption of buildings and not a consumption profile. In order to overcome this problem, statistical models has been adapted in this study which can predict the detailed consumption profile with a lower computational time comparing with analytical methods. In order to develop the model, first, a set of data has been gathered using comprehensive modeling of over 100 buildings using the TRNSYS and DOE. Results obtained from comprehensive modeling have been used subsequently for training and testing the model.

### 2.1 Reference Building

A reference building that has been used in this study is a verified small multi-unit residential building form DOE. The building has a foot-print of 20000 ft<sup>2</sup> and includes 8 different zones located in two stories above ground level,

without any basement. The building has been designed based on the requirements of the ASHRAE 90.1[10].

The building was assumed to be ventilated the entire day, and with the minimum outdoor air requirement at night-time. For the purpose of simplification, the occupant behaviour of the building was modeled based on the operational schedule suggested by MNECB[11].

## 2.2 Input Variables

Four different sets of data have been used in this study as an input variables for the model:

1. Metrological data,
2. Thermal properties of the building materials,
3. Building characteristic,
4. Occupants' pattern and behavior.

Since the main goal of the study is to represent the model that could predict the detail energy consumption profile of the users, detail hourly data has been used for the first set. TMY, weather data collected from Dorval international airport station is used for the simulation. Since heating and cooling will not occur simultaneously in residential buildings with low internal heat generation it is logical to separate the cooling and heating profiles from each other. To do so, a temperature set point had been defined as a cooling/heating threshold and the difference between the set-point and the dry bulb outdoor temperature has been used as an input file for the model. This temperature set-point for the reference building is assumed to be 21°C in this study.

Two group of buildings are considered this study; residential and office. For a residential building with low occupancy density and 24 hours operational schedule, the effect of internal heat generation on energy consumption profile of the building is less, and more uniform. Conversely for a commercial building with higher occupancy density, this effect becomes more significant. Also, in commercial buildings, this effect is limited to shorter period of time; the operational period of the building. Since internal heat generation is mainly a function of human behaviours and it varies from day to day and building to building, in this study the typical design schedule suggested by MNECB has been used. For instance, for the reference building the following schedule has been used:

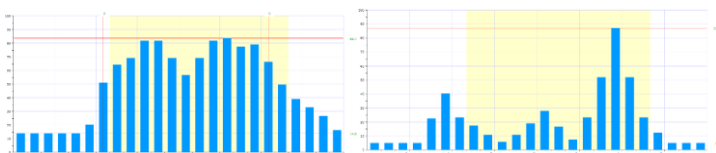




Figure 1: Internal Heat Generation Schedule for the Reference Building from left to right: Electricity; Cooking; Lighting and Occupancy

Equivalent thermal resistance and solar gain surface of a building are also considered in the development of the model. Different codes and regulations exist for the optimal value of the thermal resistance of a building, R-Value, for different building assemblies based on its application (residential commercial or etc.), and also its design methods, passive or active buildings. In order to take into account for the total heat exchange that occur between indoor and outdoor environments, the equivalent R-Value of the building has been used in this study.

$$R_{Equ.} = \sum_{i=1}^n \frac{A_{total}}{\left(\frac{A_i}{R_i}\right)} \left[\frac{m^2 \cdot ^\circ C}{W}\right] \quad (4)$$

where  $A_{total}$  is the total exterior façade of the building and  $A_i$  and  $R_i$  are the area and thermal resistance of each assemblies. Even though this number could be different from building to building, but in small communities where all the buildings have almost similar construction materials, the R-Values are almost the same. In addition, this value for newly built constructions is quite close to the one suggested by the codes. The equivalent solar gain area of the building is calculated using the following equation:

$$SGA_{Equ.} = \sum_{i=1}^n A_i \cdot (1 - \alpha_i) + AW_i \cdot \tau_i$$

where  $A_i$  is the area of each opaque assemblies,  $\alpha_i$  is the albedo of that assemblies,  $AW_i$  is the windows area and  $\tau$  is the transmittance of that window. The other parameters that influences the building load and can help to regulate the indoor thermal condition is the thermal mass of the building. A study done by Pfafferoth [12] shows that the building with a higher thermal mass can better regulate the interior temperature fluctuation and sustain it for longer period of time. In this study in order to take into account the thermal mass of the buildings, the time history method has been used.

The last set of data that has been used in the development of the procedure is the building geometry, which represents the physical geometry of a building. Properties such as orientation, shape factor, window to wall ratio, and volume of the building are considered geometrical properties of a building.

Unlike the other two categories of input variables, geometrical properties can completely change from one building to another one. To identify the effects

of these parameters on the energy consumption of building, sensitivity analysis had been performed. In order to perform the sensitivity analysis, 100 different cases have been defined and detail modeling has been executed: from these 100 buildings, in first 60 cases, one parameter has been changed at a time to study the effect of each of these parameters on the energy demand of the building. However in order to study the effect of changes of more than one parameter on the energy consumption of the buildings, in last 40 cases, the effects of combined changes on parameters on energy demand have been studied. This results, later on have been used adjusting the results for buildings other than reference building.

### 2.3 Simplified Model

Two different autoregressive time series model based on simple exponential smoothing method have been used to develop a simplified model for predicting the energy demand of the CDS. These two methods are:

1. NARX, Nonlinear Autoregressive Model with External Input, which is defined as:

$$Y(t)=f(X(t-1),...,X(t-d),Y(t-1),...,Y(t-d)) \quad (2)$$

2. Nonlinear Input-Output model which predict  $Y(t)$  given  $d$  past values of series  $X(t)$

$$Y(t)=f(X(t-1),...,X(t-d)) \quad (3)$$

For the purpose of validation, Root Mean Square Error (RMSE) has been used as an indicator to evaluate the correlation between the predicted value using the proposed method and the results obtained from comprehensive modeling using the software. The RMSE indicator defined as:

$$RMSE = [\frac{1}{m} \sum_{i=1}^m (\hat{Y}_i - Y_i)^2]^{0.5}$$

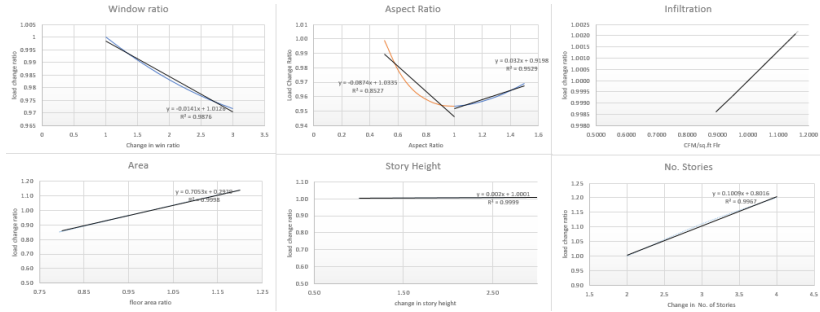
where  $\hat{Y}_i$  is the predicted value obtained from the proposed method and  $Y_i$  is the result of the comprehensive simulation and  $m$  is the number of observation.

### 2.4 ANN

ANN time series MATLAB tool box has been used for the time series autoregressive analysis. This method has an ability to predict or approximate the result of any arbitrary complex linear or non-linear system which has no or very complex analytical relation. One of the most curtail steps in using the ANN method is to define the structure of the system. Having the sufficient input/output data for training validation and testing the system, the next step is to define the number of the hidden layers as well as time delay of the system. There is no exact answer for the number of the hidden layers required for the system however, Lu and Viljanen [13] suggested the best number of the hidden layers is equal with one plus two times of the input layers.

### 3. Results

The simulation data generated from comprehensive modeling of the 100 buildings using TRNSYS and DOE was used to train the model as well as sensitivity analysis. Results obtained from sensitivity analysis have been tabulated in Figure 2.



Results of the sensitivity analysis shows the linear relation energy consumption and change in each of buildings characteristic parameters. The demand profile of the buildings have been used for modeling the system is varied from one building to another building, in order to increase the accuracy of the modeling, all the results have been used for training the system have been normalized using the following equation:

$$(a-\min)/(\max-\min)=(b+1)/(1+1) \quad (4)$$

where a is the value we want to normalize and b is the normalized value. Also to validate the trained network, results obtained from reference building, have been used. Results obtained from training of the system using two different methods are is tabulated in Table 1.

Table 1:Results Obtained from Training the System (Top) NARX (Bottom) Nonlinear

	MSE	R
Training	1.260647E+01	9.96933E-01
Validation	1.162858E+01	9.97247E-01
Testing	1.357195E+01	9.96696E-01
	MSE	R
Training	3.48258E+02	9.11375E-01
Validation	3.57561E+02	9.09341E-01
Testing	3.70603E+02	9.08390E-01



Comparing the results obtained from two different model shows not only the networked trained based on the NARX model has a lower MSE and consequently higher accuracy in predicting the demand profile of the system but also its computational time is much less than the network trained based on nonlinear input output model. As a result, network trained based on NARX model has been used for predicting the demand profile. After training the network in order to check the accuracy of the system, demand profile of three buildings which have been not used during the training process of the network have been predicted.

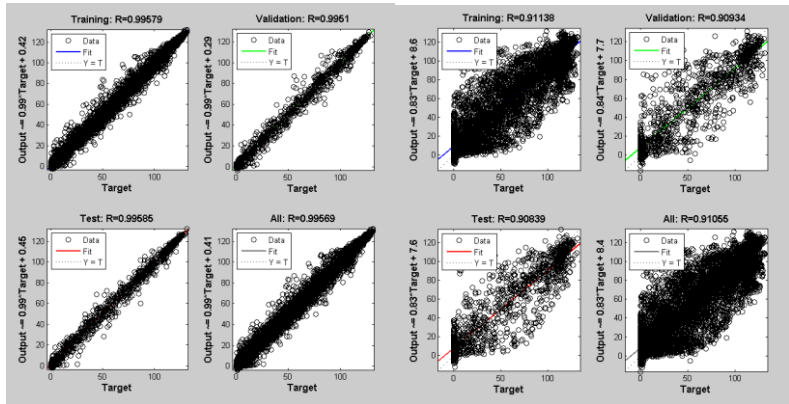


Figure 3: Regression Results Obtained from ANN (Left) NARX model; (Right) Nonlinear

Predicted results for the demand profile of each of these three building, consequently compared with the actual demand profile of them obtained from comprehensive modeling of them in DEO. Having both predicted and actual demand profile of each building, the mean square error as well as regression value for each building calculated separately which have been tabulated in Table 2

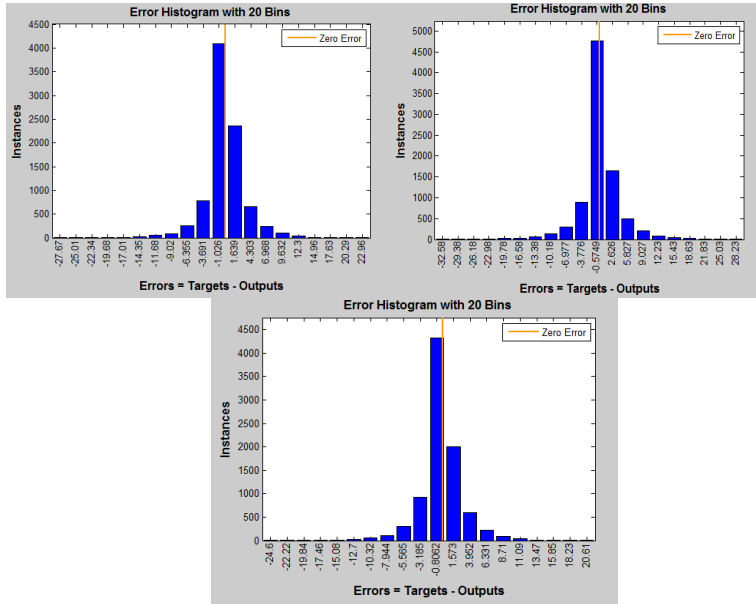
Table 2: Results for the Tested Building

Building Number	MSE	R
BLDGC4	1.86777E+01	9.95511E-01
BLDGC10	9.53027E+00	9.96818E-01
BLDGC23	1.17470E+01	9.96915E-01

Since network has been trained based on normalized results obtained from the system, predicted demand profile, should be converted back to its original format. To do that, results obtained from sensitivity analysis as well as

equation 1 could be used. After converting the predicted demand profile of the three tested building the error histogram of each profile calculated. Figure 4 shows the error histogram of the tested buildings. As illustrated in figure 4, there is a good agreement between the predicted and actual profile of all three buildings, and even though there are some outlier results exist but the frequency of them is too low and negligible.

*Figure 4 : Error Histogram of the Tested Building*



Also investigation of the time of occurrence of the outliers shows that they occur mostly in the beginning or at the end of the heating season which the heating demand become close to zero. As a results they won't affect the maximum energy demand of the system.

#### 4. Conclusion:

There are different models suggested for predicting the energy demand of the buildings especially for large scale CDS. One of the main drawbacks of these models is, most existing model only focus on the total energy consumption of the users not the demand profile and secondly the computational time and amount of information required for modeling is too high. To overcome the problem two different autoregressive time series model has been used in this

paper. Between suggested models, the NARX shows better results as well as higher computational time. After training the system, energy demand profile of the three sample building has been predicted using the suggested method. Predicted demand profile obtained from the model compared with the actual profile and shows the good agreement between them.

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